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The Role of Credit in Predicting US Recessions

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Abstract

We study the role of credit in forecasting US recession periods with probit models. We employ both classical recession predictors and common factors based on a large panel of financial and macroeconomic variables as control variables. Our findings suggest that a number of credit variables are useful predictors of US recessions over and above the control variables both in and out of sample. Especially the excess bond premium, capturing the cyclical changes in the relationship between default risk and credit spreads, is found to be a powerful predictor of recession periods.

Keywords: Business cycle, Credit Spread, Factor models, Forecasting, Probit models

JEL classification: C22, C25, E32, E37

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1 Introduction

The role of credit in business cycle fluctuations and financial crises has been a widely covered topic after the most recent financial crisis (see, e.g., Schularick and Taylor (2012) and Jorda (2014)). These papers focus on the historical role of credit and study how credit cycles and business cycles have coincided. Schularick and Taylor (2012) examine the behavior of financial, monetary and macroeconomic indicators in 14 countries with annual data starting in 1870, and uncover a key finding that exuberant credit growth has a tendency to precede financial crises. In a related vein, the role of credit spreads in predicting real activity has also attracted the interest of researchers. Theoretical frameworks on the relationship between credit spreads and economic activity have been presented by, e.g., Bernanke et al. (1999) and Philippon (2008), both of which relate the widening of credit spreads with economic downturns. Empirical studies have also evaluated this relationship, and found that credit spreads have significant predictive ability on business cycle fluctuations (see, e.g., Gilchrist and Zakrajsek (2012) and Faust et al. (2013)).

The purpose of this paper is to study the role of credit and credit spreads in predicting US recessions. Following the previous research, we employ binary response models to predict the state of the business cycle (see, e.g., Estrella and Mishkin (1998), Kauppi and Saikkonen (2008), Nyberg (2010), and Christiansen et al. (2014)). The previous literature on predicting recessions has identified a number of leading indicators for assessing the risk of economic downturns, and especially the role of financial variables has been highlighted. In particular, the predictive power of the term spread on recession periods has been studied in a number of studies since Estrella and Hardouvelis (1991), who find that it has strong predictive power on future changes of real economic activity and recession periods in excess of variables such as short term interest rates and lagged real output. Further studies, such as Estrella and Mishkin (1998), Nyberg (2010), and Ng (2012), have reaffirmed the findings concerning the term spread and also suggested that stock returns are useful leading indicators of recession periods.

While previous studies have already considered some credit variables as predictors (see, e.g., Ng (2012) and Saar and Yagil (2015)), our aim is to provide a more comprehensive look at the role of credit in predicting US recessions. We select our predictors based on previous studies on the relationship between credit and economic activity. Following Schularick and Taylor (2012), we use different measures of bank credit that describe credit growth.[1] Secondly, we employ credit spreads, such as the "GZ credit spread," a corporate credit spread index introduced by Gilchrist and Zakrajsek (2012), who find that it has considerable predictive power for business cycle fluctuations. Finally, we follow Cole et al. (2008), who use bank stock returns as a measure of general conditions in the banking sector and find that they are a significant predictor of future economic growth.

Methodologically, we follow the footsteps of Christiansen et al. (2014), who study the role of sentiment variables in predicting US recessions using factor-augmented probit models (see also Chen et al. (2011) and Bellégo and Ferrara (2012)). This approach is particularly compelling, because it allows to control for the effects of classical recession predictors and common factors based on a large panel of financial and macroeconomic variables, thus providing more robust results than traditional methods. Methodological advances have also been proposed by Kauppi and Saikkonen (2008), who introduce dynamic extensions to the standard static probit models and find that they are able to improve forecasts of recession periods. Based on these extensions, we also experiment with an autoregressive specification of the factor-augmented probit model.

Our in-sample findings indicate that credit variables are indeed useful predictors of US recessions. This result applies even after including classical recession predictors and common factors from a large panel of predictors as control variables. The out-of-sample results generally affirm these findings. In particular, we find that the so-called excess bond premium, capturing the cyclical changes in

[1] There are obvious similarities in our approach compared to that of Schularick and Taylor (2012), i.e. the focus on credit variables and the use of binary response models. However, there are also some key differences. They use a panel model with annual data to predict financial crises for 14 countries, whereas we use monthly data and focus on US business cycle recession periods. Financial crises and recessions naturally coincide in many cases, but as financial crises are even more uncommon events than recessions, focusing only in financial crises in a single country study is not feasible. For instance, the dataset used by Schularick and Taylor (2012) contained only two financial crisis periods in the post-WWII sample.

the relationship between default risk and credit spreads, is a powerful predictor both in and out of sample. Overall, the best forecasting performance is found using models that combine credit variables with classic recession predictors and common factors. Finally, we find autoregressive probit models containing credit variables and classic recession predictors, such as the yield spread and stock market returns, able to improve in-sample fit moderately.

The rest of the paper is organized in the following way. In Section 2, we describe the econometric framework and various goodness-of-fit measures. In Section 3, we present the credit variables and other predictors used in the study. In Section 4, we report the in-sample and out-of-sample results. Finally, Section 5 provides the concluding remarks.

2 Econometric methodology

In this section we present the econometric framework and discuss goodness-of-fit measures related to the binary response models. In some of our models, we use common factors constructed from a large panel of macroeconomic and financial variables as predictors. In these cases, we employ a two-step procedure where we first extract the factors using a standard factor model (see e.g. Stock and Watson (2002)), and then include these factors as predictors in the probit model. Therefore, we will also describe the static factor model below.

2.1 Factor-augmented probit model

We are interested in predicting the state of the US economy, defined as a binary indicator

$$y_t = \begin{cases} 1, \text{if the economy is in a recession,} \\ 0, \text{if the economy is in an expansion.} \end{cases} \tag{1}$$

In the previous research, binary response models, such as logit and probit models, have been used to examine the predictability of recession periods in the US and other countries. To determine the conditional probability of a recession

(p_t), a univariate probit model is specified as

$$p_t = P_{t-1}(y_t = 1) = \Phi(\pi_t), \tag{2}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and π_t is a linear function of the variables in the information set Ω_{t-1}. In the most commonly used model, the so-called static probit model, π_t is specified as

$$\pi_t = \omega + \boldsymbol{x}'_{t-k}\boldsymbol{\beta}, \tag{3}$$

where ω is a constant term and $\boldsymbol{x}_{t-k}$ includes the k:th lagged values of the explanatory variables. The parameters of the probit model can be estimated using the method of maximum likelihood (ML). For more details on the ML estimation and the computation of Newey-West-type robust standard errors, we refer to Kauppi and Saikkonen (2008) and de Jong and Woutersen (2011).

In this paper, we consider three groups of predictive variables. Our main interest is on a set of credit variables discussed in more detail in Section 3.1, but we also employ a set of classic recession predictors as well as common factors based on a large panel of financial and macroeconomic variables. The extraction of the common factors follows a standard procedure used in the previous literature (see, e.g., Stock and Watson (2002) and Christiansen et al. (2014)). Let Z_t be a $T \times N$ panel of macroeconomic and financial variables with individual elements z_{it}. A factor representation of the data is given by

$$z_{it} = \Lambda'_i F_t + e_{it}, \tag{4}$$

where F_t is a $r \times 1$ vector of common factors, Λ_i is a $r \times 1$ vector of the factor loadings, and e_{it} is an idiosyncratic error term. We use the IC_2 criterion of Bai and Ng (2002) to select the optimal number of factors for explaining the common variations in the panel. The factors are discussed in more detail in Section 3.2. In some models, we also study whether factors based on the credit variables are useful predictors. In these cases, the credit factors are also constructed in using the procedure described above.

Collecting the credit variables in the vector $\boldsymbol{x}_{t-k}$, classic recession predictors in $\boldsymbol{c}_{t-k}$, and common factors in $\boldsymbol{f}_{t-k}$, we can rewrite model (3) as

$$\pi_t = \omega + \boldsymbol{x}'_{t-k}\boldsymbol{\alpha} + \boldsymbol{c}'_{t-k}\boldsymbol{\beta} + \boldsymbol{f}'_{t-k}\boldsymbol{\gamma}, \tag{5}$$

where ω is a constant term and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ are the coefficient vectors of the lagged explanatory variables included in $\boldsymbol{x}_{t-k}$, $\boldsymbol{c}_{t-k}$ and $\boldsymbol{f}_{t-k}$, respectively.

We also consider a dynamic extension to the static probit model (5). More specifically, we consider a first-order autoregressive probit model of Kauppi and Saikkonen (2008) that was found by Nyberg (2010, 2014) to outperform static models in predicting US and German recessions. In the model, the lagged value of the linear function π_t is included in order to introduce an autoregressive structure

$$\pi_t = \omega + \alpha_1\pi_{t-1} + \boldsymbol{x}'_{t-k}\boldsymbol{\alpha} + \boldsymbol{c}'_{t-k}\boldsymbol{\beta} + \boldsymbol{f}'_{t-k}\boldsymbol{\gamma}. \tag{6}$$

Further extensions to the standard probit model have also been proposed, but as the main idea of this study is to focus on the role of credit variables in predicting US recessions, we limit our analysis to the aforementioned models.

2.2 Goodness-of-fit measures

In recent years, a number of advances have been made in the evaluation methods of probability forecasts for binary dependent variable models. Lahiri and Wang (2013) provide a review of the traditional evaluation methods as well as more recent advances in the context of evaluating probability forecasts of GDP declines. In order to take into account the multiple aspects of forecast quality, we employ a number of different goodness-of-fit measures discussed below.

One of the most commonly used measures to evaluate probability forecasts is the quadratic probability score (QPS), defined as

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(y_t - p_t)^2. \tag{7}$$

This measure can be seen as a mean square error type of statistic for binary dependent variable models and it takes on values from 0 to 2, with score 0 indicating perfect forecast accuracy.

Another commonly used measure is the pseudo-R^2 of Estrella (1998), which is a counterpart of the coefficient of determination (R^2) designed for binary response models. The measure is given by

$$psR^2 = 1 - \Big(\frac{logL_u}{logL_c}\Big)^{-(2/T)logL_c}, \tag{8}$$

where $logL_u$ and $logL_c$ are the maximum values of the constrained and unconstrained log-likelihood functions respectively, and T is the sample size. This measure takes on values between 0 and 1, and can be interpreted in the same way as the coefficient of determination in the usual linear predictive regression model. In Section 4, we also report the adjusted form of (8) (see Estrella (1998)) that takes into account the trade-off between improvement in model fit and the use of additional estimated parameters.

Due to the binary nature of the dependent variable, we also report the success ratio (SR), which is simply defined as the percentage of correct signal forecasts. A signal forecast for the state of the economy y_t can be written

$$\hat{y}_t = \mathbf{1}(p_t > \xi), \tag{9}$$

where the conditional probability of recession p_t is implied by a probit model. If p_t is larger than the threshold ξ, we get a signal forecast $\hat{y}_t = 1$ (i.e. recession), and vice versa $\hat{y}_t = 0$ if $p_t \leq \xi$. To test the whether the value of SR is higher than the success ratio obtained when the realized values y_t and the forecasts $\hat{y}_t$ are independent, Pesaran and Timmermann (2009) have suggested a predictability test (denoted PT) that also takes into account possible serial correlation in y_t.

In this paper, we report the success ratios implied by $\xi = 0.5$. Although $\xi = 0.5$ is a natural threshold in (9), it is not a fully objective selection, because the success ratios and market timing tests are highly dependent on the selected threshold. Therefore, we also look at an alternative approach to assess the accuracy of probability forecasts, namely the Receiver Operating Characteristic (ROC) curve, which has recently been used in a growing number of economic applications (see, e.g., Berge and Jorda (2011); Schularick and Taylor (2012); Lahiri and Wang (2013); Christiansen et al. (2014)). The ROC curve is a mapping of the true positive rate

$$TP(\xi) = P_{t-1}(p_t > \xi | y_t = 1) \tag{10}$$

and the false positive rate

$$FP(\xi) = P_{t-1}(p_t > \xi | y_t = 0), \tag{11}$$

for all possible thresholds $0 \leq \xi \leq 1$, described as an increasing function in $[0, 1] \times [0, 1]$ space, with $TP(\xi)$ plotted on the Y-axis and $FP(\xi)$ on the X-axis. A ROC curve above the 45-degree line indicates forecast accuracy superior to a coin toss.

The area under the ROC curve (AUC) summarizes the predictive information of the ROC curve and is defined as the integral of the ROC curve between zero and one. Therefore, the AUC also gets values between 0 and 1, with the value of 0.5 corresponding a coin toss and the value 1 to a perfect forecast. Any improvement over the AUC=0.5 indicates statistical predictability. We test the null hypothesis of AUC= 0.5 implying no predictability using standard techniques (see Hanley and McNeil, 1982), applied recently by Berge and Jorda (2011) and Christiansen et al. (2014), among others, in economic applications.[2]

3 Data

Our dependent variable is the indicator variable of the state of the US business cycle (1). The turning points are based on the official US business cycle chronology of the NBER's Business Cycle Dating Committee. In terms of explanatory variables, our main interest is on the role of credit variables and, in particular, their potential additional predictive power over and above classical recession predictors and common factors constructed from a large panel of macroeconomic and financial variables.

[2]However, Hsu and Lieli (2014) have recently shown that in the time series context, under the null hypothesis of AUC=0.5, the AUC does not follow the usual asymptotic normal distribution (cf. Berge and Jorda (2011)) and even bootstrap-based inference produces misleading results. Thus, there is a need for further theoretical work to develop a proper testing procedure in the time series context, and the test results in Section 4 should be interpreted with caution.

3.1 Credit variables

The focus on credit variables in recession forecasting is motivated by a number of recent studies that have emphasized the relationship between business cycles and credit growth or credit spreads. There is a number of credit and credit spread variables readily available without publication lags, making them ideal candidates for real-time predictors of economic activity.

There is a body of both theoretical and empirical work discussing the relationship between financial factors and the business cycle. Financial factors may propagate and amplify business cycles (see, e.g., Bernanke et al. (1999) for a discussion on this so-called financial accelerator theory). An implication of this theory is that a widening of credit spreads is associated with downturns, which motivates the use of credit spread variables in predicting recession periods. The most commonly used credit spread variable in business cycle (and asset price) forecasting applications is the default spread (SBA), defined as the difference between the Baa and Aaa -rated corporate bond yields, and we also include it in the set of potential predictors. [3]

Gilchrist and Zakrajsek (2012) construct a new credit spread index called the "GZ credit spread" (GZ), defined as the average credit spread on unsecured bonds issued by US non-financial firms.[4] In their study, the index had considerable predictive power for future economic activity, making it a natural candidate predictor of US recessions. Gilchrist and Zakrajsek (2012) also decompose this high-information content credit spread into two components. The first component represents the systematic (countercyclical) movements in the default risk of individual firms, whereas the residual component, called the excess bond premium (EBP), captures variation in the price of carrying exposure to the US corporate credit risk in excess of the compensation for the probability of default. In other words, the

[3]We also experimented with the predictive ability of the changes in Baa- and Aaa-rated bond yields, but the initial findings were not as promising as for SBA, so they were left out. Plots for the SBA and the other employed credit variables with recession bands are available in the Appendix.

[4]The data for the GZ credit spread is obtained from Simon Gilchrist's homepage: http://people.bu.edu/sgilchri/Data/data.htm.

EBP represents cyclical changes in the relationship between default risk and credit spreads. For the details on the GZ credit spread index, we refer to Gilchrist and Zakrajsek (2012). Due to the favourable evidence in terms of predictive ability on economic activity presented in their article, we also use the excess bond premium component as a predictor. The data is available from January 1973 to the end of 2012, which also determines the sample used in our study.

Schularick and Taylor (2012) study the role of changes in aggregate bank loans and assets in predicting periods of financial crises, and find that past credit growth emerges as the most useful predictor of future financial instability. They also consider loan-money and asset-money ratios. Because data on bank loans and money aggregates are available at the monthly frequency, we are also able to use these measures in our study. We use three different measures of bank loans (in logarithmic differences): the total bank credit (TBC), total consumer credit (TCC), and total real estate loans (REL), obtained from the Federal Reserve Economic Data (FRED) database.[5]

We also consider the use of bank stock returns (BS) as a measure of credit market conditions. Cole et al. (2008) find a significant relationship between bank stock returns and future economic growth that is independent of the relationship between general market returns and future GDP growth. Bank stock returns not only contain information on the current bank assets, liabilities and credit activities, but also on expectations of their future changes. Therefore, based on the previous literature linking credit to economic growth, bank stock returns should also be a good indicator of future economic growth. We use the value-weighted monthly return on the Financial industry portfolio as the bank stock return variable. The series is obtained from the Kenneth French CRSP Data Library[6] and it includes also insurance and real estate firms.

The contemporaneous correlations between the different credit variables are

[5]website: http://research.stlouisfed.org/fred2. Based on results of Schularick and Taylor (2012), we also experimented with bank asset variables and the loan-money and asset-money ratios, but these were found to have little predictive power on NBER recessions, so in order to limit the number of variables, they were left out from the final set of predictors.

[6]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

presented in the first panel of Table 1. They are not, in general strongly correlated. However, the excess bond premium (EBP) is a component of the GZ credit spread and they have a correlation of 0.654, which is high, but still not close to being perfect. As measures of the corporate bond yields, these variables are also correlated with the default spread (SBA). The total consumer credit (TCC) and real estate loans (REL) are a included in the total bank credit (TBC), and the contemporaneous correlation between TBC and REL is 0.629.

3.2 Other variables

We are interested in studying the additional predictive ability of credit variables over and above the predictive power contained in other macroeconomic and financial variables. Therefore, we have selected a number of commonly used predictors of US recessions as control variables. Several studies have suggested that financial variables are useful predictors of real activity and recessions (see, e.g., Stock and Watson (2003)). Among the most useful financial leading indicators are the term spread (TS) and stock returns (LSP) (see, e.g., Estrella and Mishkin (1998) and Nyberg (2010)). Therefore, these predictors are obvious choices as additional predictors. The term spread is defined as the difference between the 10-year US government bond yield and the 3-month Treasury Bill, whereas the stock return variable is the logarithmic first difference of the S&P500 Index. Also the short term interest rate has been found a useful predictor of recessions. We use the Federal Funds rate (FFR) as the short interest rate, following Estrella and Hardouvelis (1991), Wright (2006), and Christiansen et al. (2014). Finally, based on the promising findings of Christiansen et al. (2014), we also include a sentiment variable in the set of classic recession predictors. We experimented with both the University of Michigan Consumer Sentiment Index (CSI) and the Institute of Supply Management's Purchasing Managers Index (PMI), and found that the CSI performs better as a predictor in our sample 1973M1–2012M12. Therefore, the CSI is included as the sentiment variable in the set of recession predictors.[7]

[7]The source for the interest rate variables and the University of Michigan Consumer sentiment index (UMSCENT extended) is the FRED database and the S&P500 index is obtained from the

In addition to the classical recession predictors, we follow the approach of Christiansen et al. (2014) who consider the use of common factors based on a large panel of macroeconomic data as predictors of US recessions. We use a panel of 180 macroeconomic and financial variables that represent data from the following groups: Interest rates, stock markets, exchange rates, output and income, labour markets, housing, money, and prices. The panel is based on variables used in Ludvigson and Ng (2009) and Christiansen et al. (2014), and the variables and their transformations are discussed in detail the Appendix. For the panel of 180 series, the IC_2 criterion of Bai and Ng (2002) selects 17 factors when the maximum number of factors is set to 25, i.e., these 17 factors are able to capture a significant part of the overall variation in the variables included in the panel.[8]

Principal component analysis is often criticized on the basis of the difficulties of interpreting the factors. In our case, we are not interested in the factors in themselves, but rather the predictive information contained in credit variables in excess of the control variables. However, in order to provide some information on the factors used as predictors, we examined their correlations with the variables included in the panel. First of all, we find that the first factor (f_1) is highly correlated with the stock market variables. For example, the correlation between f_1 and the Fama-French Market Risk Factor is 0.965. The second factor (f_2) is negatively highly correlated with the Purchasing Managers' Composite Index (-0.777), whereas f_3 is positively correlated with production and employment variables and negatively with interest rates. Finally, f_6 is negatively correlated with the term spread (-0.665) and other interest rate spreads. Overall, the correlations presented above imply that the employed factors incorporate information from different types of variables from the panel, thus providing a robust set of control variables.

Goyal and Welch (2008) dataset, http://www.hec.unil.ch/agoyal/.

[8]However, although the IC_2 criterion selects 17 factors, four of the factors already explain over 50% of the variation in the panel. Further details on this issue are also found in the Appendix.

4 Empirical findings

In this section, we present the empirical results of our study. We proceed in the usual way, by first presenting findings from in-sample estimations and then discussing out-of-sample forecasting results. We examine the role of the credit variables using different specifications of the probit model. We follow the footsteps of Christiansen et al. (2014) by considering both classical recession predictors and factors based on a large macroeconomic panel as control variables. Finally, we also consider constructed factors based on the set of credit variables to find out if the predictive information contained in them can be summarized in a small number of factors.

4.1 In-sample results

The in-sample estimation period consists of the entire sample period from January 1973 to December 2012. We start off by taking a look at the individual predictive power of each of the predictors. In order to find the optimal lag structure, we allow for a different lag of each predictor and use the Bayesian information criterion (BIC) in selecting the lag. The maximum lag-length is set to twelve months and in order to limit the number of variables, we only consider a single lag per predictor.

The results of the single-predictor analysis are presented in Table 2. We find that most of the credit variables have some predictive power for recessions, but there are rather obvious differences between them. Especially the excess bond premium component (EBP_{t-1}) of the GZ credit spread stands out from the set of predictors with an AUC of 0.841 and a corresponding adjusted pseudo-R^2 of 0.221. The signs of the estimated coefficients of the credit variables are in line with economic theory, as higher credit spreads are positively and higher bank stock returns are negatively associated with the probability of recession. The first lags of the credit growth variables (TCC_{t-1} and REL_{t-1}) are associated negatively with the probability of recession whereas the longer lag of the total bank credit (TBC_{t-12}) is associated positively with recession probability. This can be interpreted as evidence in favor of recessions being credit booms gone bust (see Schularick and

Taylor (2012)).

As far as the classical predictors are concerned, our findings are in line with previous studies (see, e.g., Estrella and Mishkin (1998), Chauvet and Potter (2005), and Christiansen et al. (2014)). In particular, we find the University of Michigan consumer sentiment index (CSI_{t-1})a powerful predictor for US recessions with an AUC of 0.884 and an adjusted pseudo-R^2 of 0.315. Similarly, the term spread (TS_{t-12}) is a strong predictor, producing an AUC of 0.879 and an adjusted pseudo-R^2 of 0.264. The second factor ($f_{2,t-1}$) is the best predictor from the group of common factors with an AUC of 0.870 and an adjusted pseudo-R^2 of 0.347. Among the credit factors in the bottom panel of Table 2, we find the first factor[9] ($fcr_{1,t-1}$) a powerful predictor when considered individually (AUC= 0.838 and adj.psR^2= 0.225). Although the single-predictor analysis gives some indication on the predictive power of individual credit variables, in the following multivariate (multiple predictor) analysis we will assess the question in a more robust way by using models that combine credit variables and the control variables.

In Table 3, we present the results for models containing the different credit variables and the classic recession predictors, using the same lags of the variables as previously in Table 3. The findings indicate that four of the seven credit variables have predictive power that is not captured by the term spread (TS), federal funds rate (FFR), the log return of the S&P500 index (LSP), and the consumer sentiment index (CSI). Models 1 and2, including the GZ credit spread and the excess bond premium, respectively, perform the best. Model 1, including the GZ credit spread and the four classic recession predictors, delivers an AUC of 0.977 and an adjusted pseudo-R^2 of 0.615, which are considerably higher than for any of the single-predictor models. In fact, all of the models in Table 3 imply higher values of the AUC and the adjusted pseudo-R^2 than those presented in Table 2. Interestingly, our results also reaffirm the finding of Cole et al. (2008) that the bank stock return variable (BS) has additional predictive power over the market return (LSP), as they both have coefficients significant at least at the 5% level in Model 5. However, the

[9]The credit factors are constructed from the seven credit variables employed in the study. The first credit factor is highly correlated with the GZ credit spread (0.774) and excess bond premium (0.730).

logarithmic growth of total bank credit (TBC) and total real estate loans (REL), do not appear to have additional explanatory power for future recessions, as was already suggested by the single-predictor models. Also the default spread (SBA) does not improve the predictive performance of the models when controlled for the classic recession predictors.

In Table 2, we found the factors f_2, f_3, and f_6 the best individual predictors for the NBER recessions amongst the common factors, and therefore, we will use them as the second set of control variables. In Table 4, we report the findings based on the combinations of credit variables and these three common factors. The in-sample performance of these models is rather similar as in the previous case where we combined the credit variables and classic recession predictors. The model with only the three factors (M16) already performs very well (AUC= 0.982 and adj.psR^2=0.594), but including individual credit variables in the model still increases these measures in several cases. The coefficients of EBP, SBA, and BS are statistically significant at least at the 10% level (in M10, M11, and M13, respectively), and the model containing the bank stock return (M13) as a predictor performs the best based on the AUC (0.985) and the adjusted pseudo-R^2 (0.634).

Finally, in Table 5, we examine a number of multivariate models expected to have good performance based on the results so far.[10] The first column of Table 5 presents the results for the multivariate model including all the credit variables (M17). The AUC of this so-called kitchen sink model is 0.912 and the adjusted pseudo-R^2 is 0.367, indicating an improvement in model fit compared to all of the single predictor models presented in Table 2. However, the results concerning the coefficients and the statistical significance of the predictors in M17 should be interpreted with some caution, because many of the credit variables are strongly correlated (see Table 1).

In Model 18, we use the first common factor based on the seven credit variables (fcr_1) as a predictor in combination with classic recession predictors. We find that this model performs better (AUC= 0.973) than the kitchen sink model (M17), but

[10]We also experimented with models using different combinations of variables, but left them out in order to conserve space. However, the selected models in Table 5 describe the general findings rather well, and all other results are available by request.

slightly worse than the best models combining individual credit variables and the classic recession predictors (M1–M2). We also experimented with models combining credit factors and common factors from the large panel of macroeconomic variables, but the findings are less promising, and therefore we use M18 as one of our main models.

Model M19 (M20) shows the best combination of credit variables and classic recession predictors (common factors) based on the BIC. The findings indicate that the credit variables do have additional predictive power over the two sets of control variables, and that the model where credit variables are combined with common factors (M20) performs better based on the AUC and all the other employed goodness-of-fit measures. Finally, model M21 and M22 is the model combining credit variables, common factors, and classic recession predictors that receives the lowest values of the BIC. It is also the best performing model of all based on the in-sample fit (adj.psR^2= 0.712) and the AUC (0.991).

As an extension to the empirical analysis performed above, we consider a first-order autoregressive probit model (6) of Kauppi and Saikkonen (2008). The results of selected autoregressive probit models are also given in Table 5 and they indicate little to no improvement in the in-sample performance over the static probit models.[11] This applies for models where the credit variables are combined with classic recession predictors (Model M1 compared with Model ARM1) and also where we include common factors as predictors (M13 compared with ARM13). For the "optimal" model M21, we find that the AUC is marginally increased in the autoregressive specification ARM21 compared to the static specification M21. This is an interesting finding and indicates that the static probit model is adequate in our application and factors as predictors for US recessions.

[11] In the table, we have included the most important model, i.e. the ones that have performed best using the static specification (M1,M13, and M21), which describe the overall findings well. Further results for the autorgressive specification are available upon request.

4.2 Out-of-sample forecasting results

In the previous section we found that credit variables contain useful in-sample information on the US recession periods over and above the classic recession predictors and common factors extracted from a large panel of macroeconomic and financial variables. However, as previous forecasting literature has shown, good in-sample fit does not necessarily imply good out-of-sample performance. Therefore, in this section, we will examine the out-of-sample forecasting performance of our models. We use an expansive window forecasting approach with estimation samples ranging from 1973M2–1989M12 to 1973M2–2012M12 and we will report the results of four different forecasting horizons (1, 3, 6, and 12 months). The full sample period (1973M2–2012M12) contains six recessions in the US, and our relatively long out-of-sample period covers three of these.[12]

An important aspect to take into account is the fact that the NBER recessions are released with significant publication lags. The delay can be as long as 12 months, but most of the indicators that the NBER uses to determine whether the economy is in a recessionary state, are available with relatively short delays, making it possible to make reasonable assumptions even before the official announcements have been made (see Ng (2012)). For simplicity, we assume a publication lag of 3 months that has been previously used in the literature (see, e.g., Chauvet and Potter (2005); Ng (2012); Christiansen et al. (2014)), and thus discard the three last observations in each estimation period.

The findings for one-period-ahead forecasts based on each of the credit variables are presented in Table 6. They indicate that especially the excess bond premium (EBP) is a useful predictor of the NBER recession periods, and also the GZ credit spread and the default spread (SBA) perform well based on the AUC. In contrast, the total bank credit (TBC) and the real estate loans (REL) variables do not perform well in the out of sample exercise, as they receive negative values of

[12] In order to account for possible structural breaks in the data during the financial crisis of 2008–2009, we have also run the models for a shorter period excluding 2008–2012 from the out-of-sample analysis. The results remain robust for the shorter sample, as well as for a five-year rolling window forecast specification. These findings are available upon request.

the out-of-sample pseudo-R^2, and an AUC that differs statistically significantly from the 0.5 benchmark only at the 10% level. According to further results (not reported), the predictive power of most of the individual variables deteriorates when the forecast horizon increases.

In Table 7, we present the out-of-sample findings for the models including credit variables and the four classic recession predictors (M1–M8, models numbered as in the Section 4.1, see Table 3). The findings suggest that in the shorter forecast horizons (up to three months), especially models M1 and M2, including the GZ credit spread and the excess bond premium, respectively, outperform the model excluding the credit variables (M8). However, at the longer horizons, only M2 is systematically able to outperform Model 8, which indicates that the excess bond premium seems to contain valuable predictive information in predicting recessions.

Similarly, in Table 8 we report the findings for models including the credit variables and three common factors (M9–M16). An interesting general finding is that while the model fit based on the out-of-sample pseudo-R^2 is notably higher at shorter forecast horizons for the models in Table 8 than in Table 7, the situation turns around in the twelve-month horizon. This is mainly explained by the inclusion of the term spread (TS) in Models 1 to 8, which is a very important predictor at the longer-horizon forecasts. The findings in terms of the credit variables in Table 8 indicate that the model including EBP as a predictor (M10) performs particularly well in longer horizon forecasts, whereas M13 (including the bank stock returns) performs well in the shorter-horizon forecasts.

In Table 9 we present findings for selected multivariate models that illustrate different combinations of credit variables, classic recession predictors, and common factors (see Table 5 for the details of these models) as predictors. The findings suggest that the kitchen sink model (M17), i.e. the model including all of the credit variables considered in this study, performs poorly out of sample. This illustrates a common finding in forecasting studies that parsimonious models often tend to perform better out of sample than models that have a good in-sample fit. Results for Model 18 show that the combination of a credit factor (fcr_1) and the classic recession predictors does not perform particularly well out of sample, when compared with the models including individual credit variables and the classic predictors in Table 7. Generally, Models 18 to 21 all perform rather well at the one-to-three-month forecast horizons, but the performance based on the AUC and other goodness-of-fit measures deteriorates at the longer horizons. Overall, our findings indicate that Model 2 in Table 7) has by far the best out of sample performance at the longer (at least 6 months) forecast horizons. This reaffirms our previous findings on the usefulness of the excess bond premium as a predictor of US recession periods.

Finally, we also study the out-of-sample forecasting performance of the autoregressive probit model (6). In general, the findings indicate that the extended model (6) outperforms the static model (5) out of sample for certain forecast horizons, as illustrated by the autoregressive extension of Model 21 (ARM21) in the final column of Table 9. However, the evidence remains rather mixed for different models, so we are unable to conclude the superiority of either the static nor autoregressive specification.

5 Conclusions

In this paper, we have studied the role of credit in predicting US recessions by means of binary response models. Although there is a significant body of literature focusing on the relationship between credit and financial crises or real activity, our paper is the first one to comprehensively evaluate the role of credit variables in the context of predicting recessions. We have employed a number of credit and credit spread variables, and controlled for the predictive ability of classic predictors and common factors constructed from a large panel of financial and macroeconomic variables.

Our findings indicate that credit variables are indeed useful predictors of US recessions. The excess bond premium (EBP) component of a corporate bond credit spread index, capturing the cyclical changes in the relationship between default risk and credit spreads, shows particularly good predictive ability in various different model specifications. To a slightly lesser extent, measures such as the return on a bank stock portfolio (BS) are also found to be useful predictors of future recessions.

Combining credit variables with classic predictors and common factors generally result in higher in-sample fit as well as gains in out-of-sample forecasting. However, an autoregressive extension to the standard static probit model shows little to no improvement in both in-sample performance and mixed results in out-of-sample forecasts.

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Table 1: Correlations between employed variables

	GZ_t	EBP_t	SBA_t	TCC_t	BS_t	TBC_t	REL_t
GZ_t	1.000	0.654	0.370	-0.331	-0.150	-0.204	-0.152
EBP_t		1.000	0.548	-0.200	-0.146	-0.083	-0.001
SBA_t			1.000	-0.273	0.035	-0.148	-0.114
TCC_t				1.000	0.009	0.236	0.285
BS_t					1.000	-0.063	-0.043
TBC_t						1.000	0.629
	GZ_t	EBP_t	SBA_t	TC_t	BS_t	TBC_t	REL_t
TS_t	0.171	0.052	0.171	-0.099	0.055	-0.234	-0.231
FFR_t	-0.506	0.061	0.229	0.197	0.004	0.237	0.290
LSP_t	-0.218	-0.264	0.012	0.020	0.591	-0.107	-0.077
CSI_t	-0.193	-0.284	-0.492	0.347	0.071	0.253	0.157

Notes: This table presents the correlation coefficients between the employed credit variables and between the credit variables and the classic recession predictors.

Table 2: In-sample results for single-predictor probit models

	Variable	Coeff.	adj.psR^2	BIC	QPS	AUC
Credit variables						
1	GZ_{t-1}	0.397***	0.076	184.830	0.225	0.648***
2	EBP_{t-1}	1.528***	0.221	152.133	0.188	0.841***
3	SBA_{t-1}	1.190***	0.148	168.579	0.201	0.740***
4	TCC_{t-1}	-2.326***	0.087	182.328	0.234	0.734***
5	BS_{t-4}	-0.066***	0.060	188.532	0.231	0.705***
6	TBC_{t-12}	0.989**	0.017	198.536	0.251	0.633***
7	REL_{t-1}	-0.537	0.005	201.346	0.253	0.624***
Classic recession predictors						
8	TS_{t-12}	-0.676***	0.264	142.842	0.183	0.879***
9	FFR_{t-8}	0.137***	0.115	176.017	0.214	0.733***
10	LSP_{t-3}	-0.114***	0.079	184.174	0.228	0.696***
11	CSI_{t-1}	-0.078***	0.315	131.687	0.159	0.884***
Factors based on large panel						
12	$f_{1,t-4}$	-0.351***	0.051	190.580	0.237	0.674***
13	$f_{2,t-1}$	1.107***	0.344	125.246	0.137	0.870***
14	$f_{3,t-2}$	-0.589***	0.161	165.537	0.196	0.795***
15	$f_{4,t-11}$	0.318**	0.036	194.013	0.242	0.660***
16	$f_{5,t-4}$	-0.049	Neg.	203.193	0.254	0.519
17	$f_{6,t-9}$	0.544***	0.107	173.716	0.223	0.749***
18	$f_{7,t-12}$	0.246***	0.020	197.883	0.250	0.649***
19	$f_{8,t-4}$	0.074	Neg.	202.899	0.254	0.541
20	$f_{9,t-5}$	-0.204**	0.013	199.461	0.251	0.617***
21	$f_{10,t-12}$	0.083	Neg.	202.793	0.254	0.544
22	$f_{11,t-6}$	0.213**	0.016	198.748	0.248	0.609***
23	$f_{12,t-1}$	0.093	Neg.	202.525	0.253	0.512
24	$f_{13,t-10}$	0.047	Neg.	203.250	0.255	0.537
25	$f_{14,t-11}$	0.203**	0.015	199.068	0.248	0.597***
26	$f_{15,t-4}$	-0.071	Neg.	202.929	0.254	0.539
27	$f_{16,t-8}$	-0.088	Neg.	202.624	0.253	0.548
28	$f_{17,t-12}$	-0.178***	0.009	200.394	0.252	0.597***
Factors based on credit variables						
29	$fcr_{1,t-1}$	0.851***	0.225	151.384	0.185	0.838***
30	$fcr_{2,t-4}$	0.425***	0.059	188.757	0.241	0.700***
31	$fcr_{3,t-4}$	-0.224**	0.018	198.303	0.247	0.620***

Notes: This table presents the findings from single-predictor probit models for NBER recessions. The table includes findings for the credit variables as well as for the two groups of control variables. Robust standard errors of the estimated coefficients are reported in brackets (see Kauppi and Saikkonen (2008)). The goodness-of-fit measures are described in detail in Section 2.2. In the table, *, **, and *** denote the statistical significance of the estimated coefficients and the AUC at 10%, 5% and 1% significance levels, respectively. "Neg." refers to a negative value of the adjusted pseudo-R^2.

Table 3: In-sample results for credit variables and classic recession predictors

Variable	M1	M2	M3	M4	M5	M6	M7	M8
GZ_{t-1}	0.974***							
	(0.257)							
EBP_{t-1}		1.656***						
		(0.387)						
SBA_{t-1}			0.315					
			(0.349)					
TCC_{t-1}				-1.563**				
				(0.664)				
BS_{t-4}					-0.040**			
					(0.019)			
TBC_{t-12}						0.210		
						(0.553)		
REL_{t-1}							-0.456	
							(0.519)	
TS_{t-12}	-0.420***	-0.438***	-0.498***	-0.501***	-0.485***	-0.482***	-0.489***	-0.487***
	(0.136)	(0.159)	(0.168)	(0.168)	(0.160)	(0.167)	(0.163)	(0.164)
FFR_{t-8}	0.202***	0.180**	0.035	0.052	0.088*	0.042	0.050	0.044
	(0.054)	(0.039)	(0.044)	(0.045)	(0.045)	(0.044)	(0.045)	(0.044)
LSP_{t-3}	-0.082***	-0.085***	-0.109***	-0.122***	-0.078***	-0.112***	-0.115***	-0.111***
	(0.028)	(0.030)	(0.025)	(0.025)	(0.028)	(0.026)	(0.025)	(0.025)
CSI_{t-1}	-0.061***	-0.064***	-0.054***	-0.054***	-0.060***	-0.061***	-0.060***	-0.061***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)
CONST	0.771	3.444***	3.074***	3.546***	3.796***	3.885***	3.944***	3.935**
	(0.785)	(1.130)	(1.324)	(1.237)	(1.216)	(1.280)	(1.259)	(1.255)
psR^2	0.620	0.606	0.501	0.514	0.506	0.497	0.499	0.496
$adj.psR^2$	0.615	0.601	0.495	0.508	0.500	0.490	0.493	0.491
BIC	81.243	83.926	105.026	102.377	103.992	105.988	105.436	103.002
QPS	0.084	0.089	0.116	0.114	0.116	0.119	0.118	0.119
SR	0.940***	0.938***	0.912***	0.910***	0.908***	0.908***	0.912***	0.910***
AUC	0.977***	0.974***	0.958***	0.960***	0.957***	0.957***	0.957***	0.957***

Notes: This table presents the findings from probit models for NBER recessions including credit variables and classic recession predictors. In the table, *, **, and *** denote the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 10%, 5% and 1% significance levels, respectively. See also notes to Table 2.

Table 4: In-sample results for credit variables and common factors

Variable	M9	M10	M11	M12	M13	M14	M15	M16
GZ_{t-1}	0.333							
	(0.257)							
EBP_{t-1}		0.782**						
		(0.370)						
SBA_{t-1}			-0.750*					
			(0.358)					
TCC_{t-1}				0.547				
				(0.633)				
BS_{t-4}					-0.081***			
					(0.021)			
TBC_{t-12}						0.696		
						(0.580)		
REL_{t-1}							0.405	
							(0.545)	
$f_{2,t-1}$	1.112***	1.069***	1.573***	1.324***	1.361***	1.290***	1.309***	1.260***
	(0.257)	(0.274)	(0.315)	(0.223)	(0.309)	(0.249)	(0.242)	(0.242)
$f_{3,t-2}$	-1.010***	-0.887***	-1.058***	-0.894***	-0.949***	-0.845***	-0.875***	-0.879***
	(0.195)	(0.187)	(0.245)	(0.182)	(0.214)	(0.180)	(0.189)	(0.189)
$f_{6,t-9}$	0.353**	0.358**	0.341**	0.418***	0.419**	0.398**	0.412**	0.417**
	(0.155)	(0.163)	(0.155)	(0.161)	(0.160)	(0.160)	(0.164)	(0.163)
CONST	-2.592***	-2.082***	-1.287***	-2.129***	-2.046***	-2.185***	-2.117***	-1.984***
	(0.518)	(0.223)	(0.366)	(0.234)	(0.251)	(0.249)	(0.296)	(0.209)
psR^2	0.609	0.614	0.612	0.599	0.638	0.602	0.599	0.597
$adj.psR^2$	0.604	0.609	0.607	0.594	0.634	0.597	0.594	0.594
BIC	80.408	79.408	79.813	82.322	74.577	81.768	82.370	79.564
QPS	0.084	0.083	0.080	0.087	0.072	0.084	0.086	0.087
SR	0.936***	0.934***	0.940***	0.927***	0.946***	0.938***	0.929***	0.934***
AUC	0.983***	0.982***	0.984***	0.982***	0.985***	0.983***	0.982***	0.982***

Notes: This table presents the findings from probit models for NBER recessions including credit variables and common factors from a large panel of financial and macroeconomic variables. See also notes to Table 2.

Table 5: In-sample results for selected static and autoregressive models

Variable	M17	M18	M19	M20	M21	ARM1	ARM13	ARM21
GZ_{t-1}	-0.340*		1.227***			0.710		
	(0.195)		(0.296)			(2.201)		
EBP_{t-1}	1.894***			0.843**	1.372***			1.122
	(0.479)			(0.385)	(0.462)			(1.440)
SBA_{t-1}	0.495		-1.023**	-0.954***	-1.663***			-1.258
	(0.344)		(0.410)	(0.393)	(0.461)			(5.894)
TCC_{t-1}	-1.683***							
	(0.591)							
BS_{t-4}	-0.054***			-0.079***	-0.077***		-0.076***	-0.081
	(0.016)			(0.020)	(0.020)		(0.019)	(0.310)
TBC_{t-12}	1.357***							
	(0.488)							
REL_{t-1}	-0.782							
	(0.581)							
$fcr_{1,t-1}$		0.813***						
		(0.225)						
$f_{2,t-1}$				1.498***	1.099***		1.427***	0.624
				(0.376)	(0.220)		(0.256)	(9.173)
$f_{3,t-2}$				-1.204***			-0.961***	
				(0.269)			(0.138)	
$f_{6,t-9}$				0.254			0.422	
				(0.161)			(0.133)	
TS_{t-12}		-0.468***	-0.344***		-0.382**	-0.328		-0.224
		(0.225)	(0.131)		(0.152)	(0.652)		(2.536)
FFR_{t-8}		0.107***	0.291***		0.222***	0.154		0.162
		(0.035)	(0.069)		(0.061)	(0.387)		(0.867)
LSP_{t-3}		-0.118***	-0.069**			-0.085		
		(0.029)	(0.030)			(0.111)		
CSI_{t-1}		-0.044***	-0.080***		-0.077***	-0.043		-0.051
		(0.016)	(0.018)		(0.018)	(0.139)		(0.494)
π_{t-1}						0.207	-0.058	0.284
						(1.833)	(0.163)	(6.480)
CONST	-1.254*	1.819***	2.343*	-1.230***	4.896***	0.437	-2.111	3.300
	(0.668)	(1.306)	(1.372)	(0.476)	(1.503)	(2.723)	(0.322)	(29.826)
psR^2	0.378	0.590	0.642	0.668	0.717	0.604	0.625	0.694
adj.psR^2	0.367	0.585	0.637	0.663	0.712	0.598	0.620	0.688
BIC	137.184	87.0048	79.967	75.070	68.642	87.378	80.241	76.182
QPS	0.144	0.093	0.077	0.062	0.051	0.082	0.073	0.050
SR	0.906***	0.934***	0.949***	0.961***	0.968***	0.944***	0.946***	0.966***
AUC	0.912***	0.973***	0.980***	0.988***	0.991***	0.977***	0.985***	0.992***

Notes: This table presents findings from selected multivariate static and autoregreseeive probit models for NBER recessions including credit variables, common factors based on the credit variables, and control variables. In terms of notation, ARM21 is the autoregressive extension of M21. See also notes to Table 2.

Table 6: Out-of-sample results for credit variables

Model	GZ	EBP	SBA	TCC	BS	TBC	REL
psR^2	0.043	0.301	0.196	0.018	0.058	Neg.	Neg.
QPS	0.211	0.148	0.164	0.231	0.204	0.232	0.263
AUC	0.736***	0.915***	0.779***	0.681***	0.648***	0.527*	0.569*

Notes: This table presents the one-month-ahead forecasting results from static probit models for NBER recessions using credit variables as predictors. See also the notes to Table 2

Table 7: Out-of-sample results for models including credit variables and classic predictors

Forecast horizon: 1 month								
Model	M1	M2	M3	M4	M5	M6	M7	M8
psR^2	0.312	0.356	0.133	0.186	0.127	0.096	0.145	0.160
QPS	0.103	0.95	0.162	0.136	0.139	0.156	0.143	0.148
AUC	0.915***	0.930***	0.887***	0.884***	0.867***	0.873***	0.867***	0.884***
Forecast horizon: 3 months								
psR^2	0.298	0.290	0.023	0.102	0.117	0.031	0.094	0.132
QPS	0.112	0.120	0.194	0.171	0.163	0.179	0.177	0.170
AUC	0.890***	0.910***	0.842***	0.859***	0.860***	0.857***	0.862***	0.873***
Forecast horizon: 6 months								
psR^2	0.034	0.210	Neg.	Neg.	0.028	Neg.	Neg.	0.033
QPS	0.197	0.184	0.215	0.213	0.203	0.208	0.218	0.201
AUC	0.811***	0.905***	0.692***	0.668***	0.810***	0.772***	0.761***	0.793***
Forecast horizon: 12 months								
psR^2	Neg.	0.114	Neg.	Neg.	0.032	Neg.	Neg.	0.043
QPS	0.217	0.196	0.205	0.209	0.200	0.214	0.215	0.198
AUC	0.638***	0.778***	0.707***	0.707***	0.731***	0.706***	0.710***	0.738***

Notes: This table presents the one-to-twelve-month-ahead forecasting results from static probit models for NBER recessions using credit variables and classic recession predictors. See also the notes to Table 2.

Table 8: Out-of-sample results for models including credit variables and common factors

Forecast horizon: 1 month								
Model	M9	M10	M11	M12	M13	M14	M15	M16
psR^2	0.418	0.503	0.524	0.496	0.511	0.506	0.489	0.504
QPS	0.106	0.103	0.100	0.108	0.094	0.107	0.110	0.106
AUC	0.942***	0.977***	0.978***	0.981***	0.965***	0.980***	0.978***	0.981***
Forecast horizon: 3 months								
psR^2	0.114	0.234	0.228	0.240	0.300	0.244	0.247	0.249
QPS	0.157	0.151	0.176	0.172	0.139	0.171	0.171	0.171
AUC	0.804***	0.880***	0.904***	0.913***	0.891***	0.913***	0.916***	0.917***
Forecast horizon: 6 months								
psR^2	Neg.	0.145	0.017	0.046	0.140	0.065	0.076	0.070
QPS	0.214	0.191	0.216	0.213	0.196	0.213	0.212	0.210
AUC	0.645***	0.844***	0.695***	0.739***	0.831***	0.760***	0.788***	0.762***
Forecast horizon: 12 months								
psR^2	Neg.	0.049	0.012	0.024	0.038	0.025	0.023	0.042
QPS	0.222	0.214	0.220	0.219	0.218	0.218	0.221	0.217
AUC	0.567	0.750***	0.666***	0.685***	0.723***	0.685***	0.689***	0.731***

Notes: This table presents the one-to-twelve-month-ahead forecasting results from static probit models for NBER recessions using credit variables and common factors as predictors. See also the notes to Table 2.

Table 9: Out-of-sample results for selected multivariate models

Forecast horizon: 1 month								
Model	M17	M18	M19	M20	M21	ARM1	ARM13	ARM21
psR^2	0.258	0.337	0.317	0.529	0.537	0.443	0.548	0.528
QPS	0.149	0.097	0.105	0.085	0.090	0.084	0.088	0.083
AUC	0.871***	0.911***	0.918***	0.966***	0.976***	0.939***	0.986***	0.962***
Forecast horizon: 3 months								
psR^2	0.074	0.221	0.306	0.271	0.312	0.239	0.326	0.270
QPS	0.180	0.137	0.104	0.135	0.131	0.121	0.146	0.132
AUC	0.794***	0.879***	0.898***	0.882***	0.926***	0.917***	0.941***	0.904***
Forecast horizon: 6 months								
psR^2	Neg.	Neg.	0.031	0.156	0.003	0.009	Neg.	Neg
QPS	0.213	0.216	0.206	0.175	0.206	0.203	0.278	0.278
AUC	0.665***	0.755***	0.831***	0.859***	0.866***	0.815***	0.603**	0.840***
Forecast horizon: 12 months								
psR^2	Neg.	Neg.	Neg.	0.01	Neg.	Neg.	Neg.	Neg.
QPS	0.268	0.218	0.220	0.218	0.216	0.308	0.230	0.306
AUC	0.448	0.648***	0.625**	0.679***	0.697***	0.728***	0.735***	0.724***

Notes: This table presents the one-to-twelve-month-ahead forecasting results from selected multivariate (multiple predictor) probit models for NBER recessions including credit variables, common factors based on the credit variables, and control variables. ARM21 refers to the autoregressive extension of Model 21, see Table 5. See also the notes to Table 2.